Importing libraries

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Reading dataset

In [3]:
```
df = pd.read_csv('bank_data.csv')
df.head()
```

Out[3]:

	banking marketing	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unname
0	customer id and age.	NaN	Customer salary and balance.	NaN	Customer marital status and job with education...	NaN	particu custon befo target or r
1	customerid	age	salary	balance	marital	jobedu	target
2	1	58	100000	2143	married	management,tertiary	y
3	2	44	60000	29	single	technician,secondary	y
4	3	33	120000	2	married	entrepreneur,secondary	y

Data Cleaning

In [4]:
```
df = pd.read_csv('bank_data.csv', skiprows = 2)   #skip_blank_lines,skipfoot
df.head()
```

Out[4]:

	customerid	age	salary	balance	marital	jobedu	targeted	default	hc
0	1	58.0	100000	2143	married	management,tertiary	yes	no	
1	2	44.0	60000	29	single	technician,secondary	yes	no	
2	3	33.0	120000	2	married	entrepreneur,secondary	yes	no	
3	4	47.0	20000	1506	married	blue-collar,unknown	no	no	
4	5	33.0	0	1	single	unknown,unknown	no	no	

Dropping column

In [5]:
```
df.drop("customerid",axis=1, inplace=True)
df.head()
```

Out[5]:

	age	salary	balance	marital	jobedu	targeted	default	housing	loan
0	58.0	100000	2143	married	management,tertiary	yes	no	yes	no
1	44.0	60000	29	single	technician,secondary	yes	no	yes	no
2	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes
3	47.0	20000	1506	married	blue-collar,unknown	no	no	yes	no
4	33.0	0	1	single	unknown,unknown	no	no	no	no

Dividing jobedu in job and education

In [6]:
```
df['job'] = df.jobedu.apply(lambda x: x.split(",")[0])
df.head()
```

Out[6]:

	age	salary	balance	marital	jobedu	targeted	default	housing	loan
0	58.0	100000	2143	married	management,tertiary	yes	no	yes	no
1	44.0	60000	29	single	technician,secondary	yes	no	yes	no
2	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes
3	47.0	20000	1506	married	blue-collar,unknown	no	no	yes	no
4	33.0	0	1	single	unknown,unknown	no	no	no	no

In [7]:
```
df['education'] = df.jobedu.apply(lambda x: x.split(",")[1])
df.head()
```

Out[7]:

	age	salary	balance	marital	jobedu	targeted	default	housing	loan
0	58.0	100000	2143	married	management,tertiary	yes	no	yes	no
1	44.0	60000	29	single	technician,secondary	yes	no	yes	no
2	33.0	120000	2	married	entrepreneur,secondary	yes	no	yes	yes
3	47.0	20000	1506	married	blue-collar,unknown	no	no	yes	no
4	33.0	0	1	single	unknown,unknown	no	no	no	no

A new column 'Education' is added to the DataFrame df. The values are extracted from the 'jobedu' column using the apply() function with a lambda function that splits each 'jobedu' value by commas and retains the first part, which represents the education level. This new 'Education' column contains the extracted education levels from the 'jobedu' column.

Dropping the jobedu

In [8]:

```
df.drop("jobedu",axis=1, inplace=True)
df.head()
```

Out[8]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may, 2017
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may, 2017
2	33.0	120000	2	married	yes	no	yes	yes	unknown	5	may, 2017
3	47.0	20000	1506	married	no	no	yes	no	unknown	5	may, 2017
4	33.0	0	1	single	no	no	no	no	unknown	5	may, 2017

Extract the value of month from the column month

In [9]:

```
df[df.month.apply(lambda x: isinstance(x,float)) == True]
df.head()
```

Out[9]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may, 2017
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may, 2017
2	33.0	120000	2	married	yes	no	yes	yes	unknown	5	may, 2017
3	47.0	20000	1506	married	no	no	yes	no	unknown	5	may, 2017
4	33.0	0	1	single	no	no	no	no	unknown	5	may, 2017

The provided code takes a DataFrame 'df' and retrieves rows where the 'month' column holds floating-point numbers. It employs a lambda function to identify instances of floats within the 'month' column, resulting in a filtered DataFram'e.'

Missing values

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
age          20
salary        0
balance       0
marital       0
targeted      0
default       0
housing       0
loan          0
contact       0
day           0
month        50
duration      0
campaign      0
pdays         0
previous      0
poutcome      0
response     30
job           0
education     0
dtype: int64
```

Handling missing values

In [11]:
```
df.age.isnull().sum()
```

Out[11]:
```
20
```

In [12]:
```
df.shape
```

Out[12]: (45211, 19)

In [13]:
```
float(100.00*20/45211)
```

Out[13]: 0.04423702196368141

Drop records with age missing

In [14]:
```
df = df[~df.age.isnull()].copy()
df.shape
```

Out[14]: (45191, 19)

In [15]:
```
df.age.isnull().sum()
```

Out[15]: 0

Handling missing values in month

In [16]:
```
df.month.isnull().sum()
```

Out[16]: 50

In [17]:
```
df.month.value_counts(normalize=0)
```

Out[17]:
```
may, 2017    13740
jul, 2017     6885
aug, 2017     6235
jun, 2017     5333
nov, 2017     3967
apr, 2017     2930
feb, 2017     2646
jan, 2017     1402
oct, 2017      737
sep, 2017      576
mar, 2017      476
dec, 2017      214
Name: month, dtype: int64
```

In [18]:
```
month_mode = df.month.mode()[0]
month_mode
```

Out[18]: 'may, 2017'

In [19]:
```
df.month.fillna(month_mode, inplace=True)
df.month.value_counts(normalize=True)
```

Out[19]:
```
may, 2017    0.305149
jul, 2017    0.152353
aug, 2017    0.137970
jun, 2017    0.118010
nov, 2017    0.087783
apr, 2017    0.064836
feb, 2017    0.058551
jan, 2017    0.031024
oct, 2017    0.016309
sep, 2017    0.012746
mar, 2017    0.010533
dec, 2017    0.004735
Name: month, dtype: float64
```

In [20]:
```
df.month.isnull().sum()
```

Out[20]:
```
0
```

In [21]:
```
df.month.fillna(month_mode,inplace= True)
df.month.value_counts(normalize= True)
```

Out[21]:
```
may, 2017    0.305149
jul, 2017    0.152353
aug, 2017    0.137970
jun, 2017    0.118010
nov, 2017    0.087783
apr, 2017    0.064836
feb, 2017    0.058551
jan, 2017    0.031024
oct, 2017    0.016309
sep, 2017    0.012746
mar, 2017    0.010533
dec, 2017    0.004735
Name: month, dtype: float64
```

In [22]:
```
df.month.isnull().sum()
```

Out[22]:
```
0
```

In [ ]:

In [ ]:

Find duplicates

In [23]:
```
duplicate_columns = ['age', 'response']
duplicates = df[df.duplicated(subset=duplicate_columns, keep=False)]
duplicates.head()
```

Out[23]:

	age	salary	balance	marital	targeted	default	housing	loan	contact	day	month
0	58.0	100000	2143	married	yes	no	yes	no	unknown	5	may, 2017
1	44.0	60000	29	single	yes	no	yes	no	unknown	5	may, 2017
2	33.0	120000	2	married	yes	no	yes	yes	unknown	5	may, 2017
3	47.0	20000	1506	married	no	no	yes	no	unknown	5	may, 2017
4	33.0	0	1	single	no	no	no	no	unknown	5	may, 2017

In [24]:

```
df.age.nunique()
```

Out[24]:

```
77
```

In [25]:

```
df.age.unique()
```

Out[25]:

```
array([58., 44., 33., 47., 35., 28., 42., 43., 41., 29., 53., 57., 51.,
       45., 60., 56., 32., 25., 40., 39., 52., 46., 36., 49., 59., 37.,
       50., 54., 55., 48., 24., 38., 31., 30., 27., 34., 23., 26., 61.,
       22., 21., 20., 66., 62., 83., 75., 67., 70., 65., 68., 64., 69.,
       72., 71., 19., 76., 85., 63., 90., 82., 73., 74., 78., 80., 94.,
       79., 77., 86., 95., 81., 18., 89., 84., 87., 92., 93., 88.])
```

In [ ]:

In [ ]:

In [26]:

```
df.pdays.describe()
```

Out[26]:

```
count    45191.000000
mean        40.181253
std        100.074099
min         -1.000000
25%         -1.000000
50%         -1.000000
75%         -1.000000
max        871.000000
Name: pdays, dtype: float64
```

-1 indicates missing value!!!

How do we hanlde this?

Remember our objective!

- we want the missing values to be ignored in the calculations
- simply make it missing- replace -1 with NaN

- all summary statistics- mean, median, etc. will ignore the missing values

In [27]:
```
df.loc[df.pdays<0,"pdays"] = np.NaN
df.pdays.describe()
```

Out[27]:
```
count    8252.000000
mean      224.523752
std       115.202715
min         1.000000
25%       133.000000
50%       194.500000
75%       327.000000
max       871.000000
Name: pdays, dtype: float64
```

Missing value doesn't have to be present as null

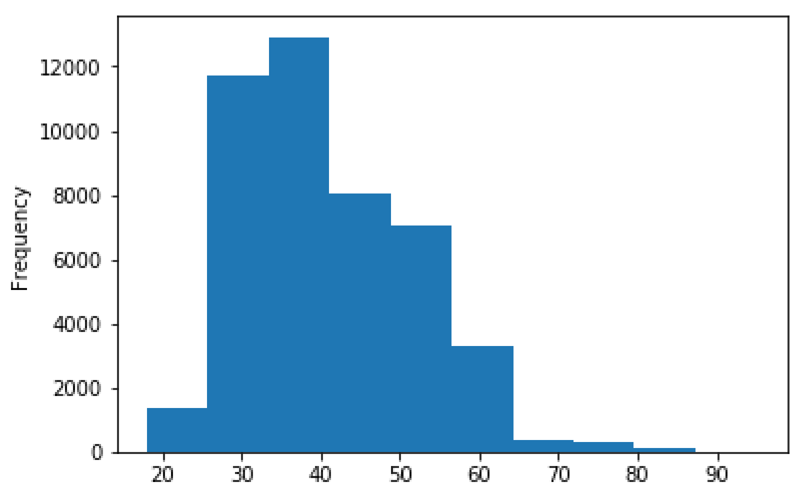
Outlier Handling

Age variable

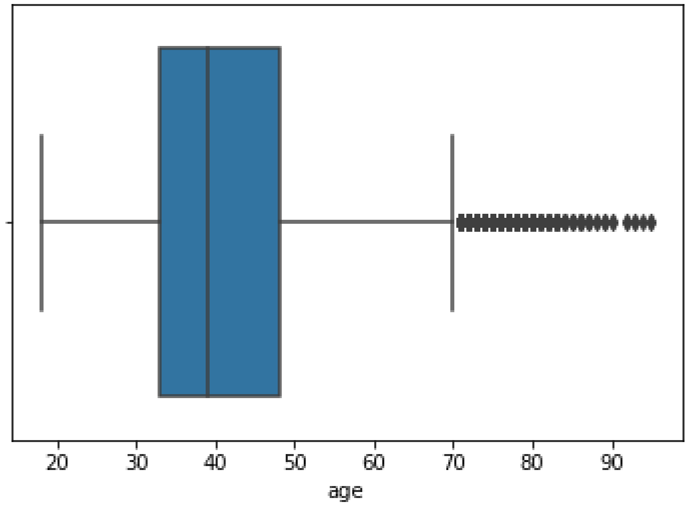
In [28]:
```
df.age.describe()
```

Out[28]:
```
count    45191.000000
mean        40.935651
std         10.619198
min         18.000000
25%         33.000000
50%         39.000000
75%         48.000000
max         95.000000
Name: age, dtype: float64
```

In [29]:
```
df.age.plot.hist()
plt.show()
```



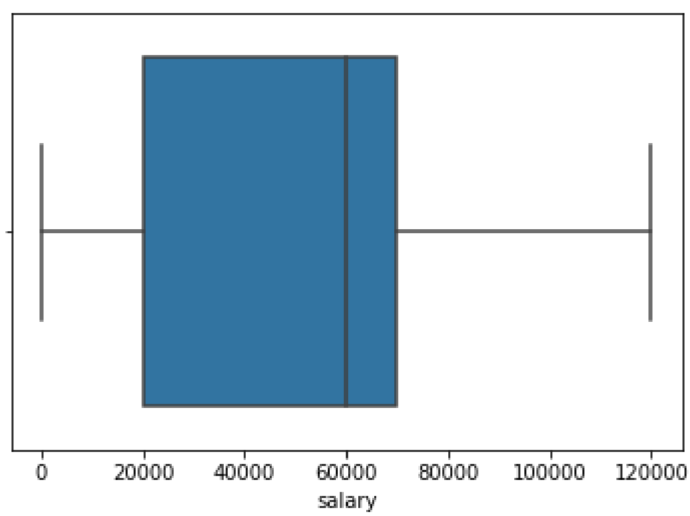
In [30]:
```
sns.boxplot(df.age)
plt.show()
```



In [31]:
```
df.salary.describe()
```

Out[31]:
```
count     45191.000000
mean      57005.974641
std       32084.253154
min           0.000000
25%       20000.000000
50%       60000.000000
75%       70000.000000
max      120000.000000
Name: salary, dtype: float64
```

In [32]:
```
sns.boxplot(df.salary)
plt.show()
```

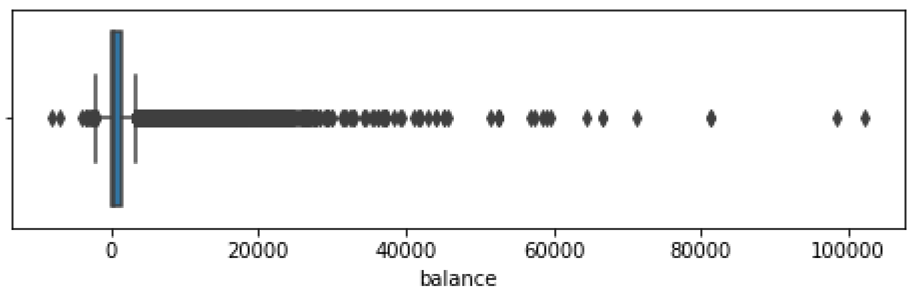


Balance Variable

In [33]:
```
df.balance.describe()
```

```
Out[33]: count     45191.000000
         mean       1362.432520
         std        3045.120417
         min       -8019.000000
         25%          72.000000
         50%         448.000000
         75%        1428.000000
         max      102127.000000
         Name: balance, dtype: float64
```

```python
In [34]: plt.figure(figsize=[8,2])
         sns.boxplot(df.balance)
         plt.show()
```




```python
In [35]: df.balance.quantile([0.5,0.7,0.9,0.95,0.99])
```

```
Out[35]: 0.50      448.0
         0.70     1126.0
         0.90     3575.0
         0.95     5768.0
         0.99    13167.1
         Name: balance, dtype: float64
```

```python
In [36]: df[df.balance>15000].describe()
```

Out[36]:

	age	salary	balance	day	campaign	pdays	
count	351.000000	351.000000	351.000000	351.000000	351.000000	62.000000	35
mean	45.341880	70008.547009	24295.780627	16.022792	2.749288	188.516129	(
std	12.114333	34378.272805	12128.560693	8.101819	3.036886	118.796388	
min	23.000000	0.000000	15030.000000	1.000000	1.000000	31.000000	(
25%	35.000000	50000.000000	17074.000000	9.000000	1.000000	96.250000	(
50%	44.000000	60000.000000	20723.000000	18.000000	2.000000	167.500000	(
75%	55.000000	100000.000000	26254.000000	21.000000	3.000000	246.500000	(
max	84.000000	120000.000000	102127.000000	31.000000	31.000000	589.000000	2:

Instead of looking at mean, we could look at quantiles/medians/percentiles instead

Standarize variable

Duration variable

In [37]:
```
df.duration.head()
```

Out[37]:
```
0    261 sec
1    151 sec
2     76 sec
3     92 sec
4    198 sec
Name: duration, dtype: object
```

In [38]:
```
df.duration.describe()
```

Out[38]:
```
count       45191
unique       2646
top       1.5 min
freq          138
Name: duration, dtype: object
```

In [39]:
```
df.duration= df.duration.apply(lambda x: float(x.split()[0])/60 if x.find("s
```

In [40]:
```
df.duration.describe()
```

Out[40]:
```
count    45191.000000
mean         4.303030
std          4.292739
min          0.000000
25%          1.716667
50%          3.000000
75%          5.316667
max         81.966667
Name: duration, dtype: float64
```

In [41]:
```
df.dtypes
```

Out[41]:
```
age           float64
salary          int64
balance         int64
marital        object
targeted       object
default        object
housing        object
loan           object
contact        object
day             int64
month          object
duration      float64
campaign        int64
pdays         float64
previous        int64
poutcome       object
response       object
job            object
education      object
dtype: object
```

Univariate analysis- Categorical features

Marital

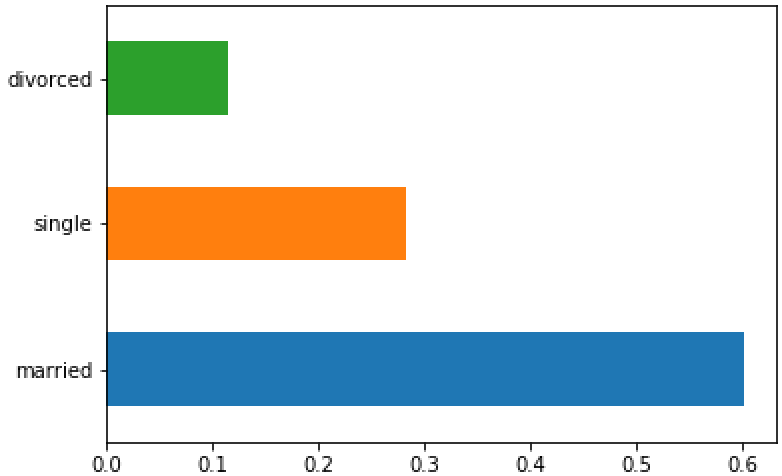
In [42]:
```python
df.marital.value_counts()
```

Out[42]:
```
married     27204
single      12786
divorced     5201
Name: marital, dtype: int64
```

In [43]:
```python
df.marital.value_counts(normalize= True)
```

Out[43]:
```
married     0.601978
single      0.282932
divorced    0.115089
Name: marital, dtype: float64
```

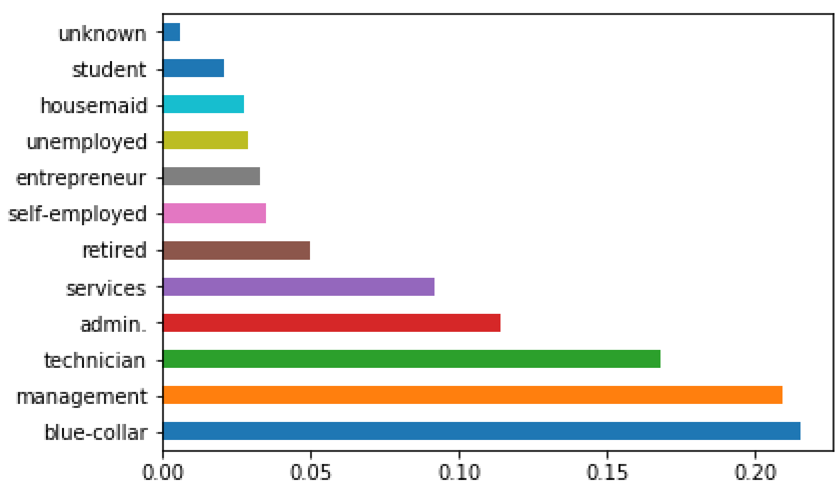
In [44]:
```python
df.marital.value_counts(normalize= True).plot.barh()
plt.show()
```



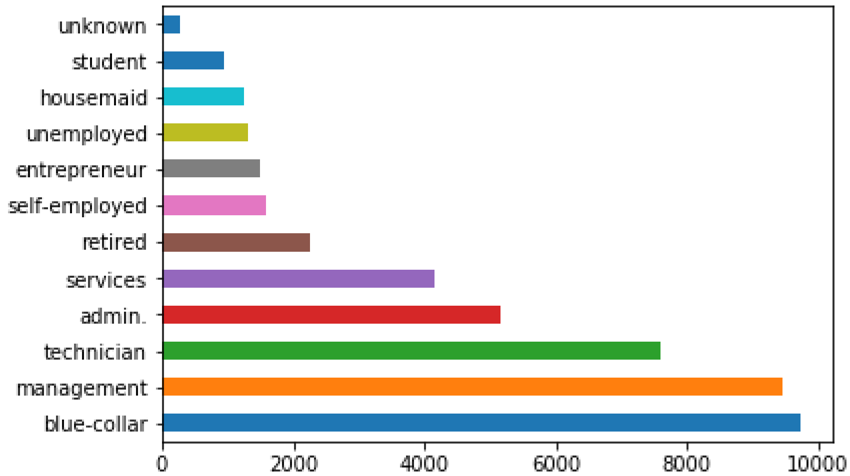
In [45]:
```
df.job.describe()
```

Out[45]:
```
count           45191
unique             12
top       blue-collar
freq             9727
Name: job, dtype: object
```

In [46]:
```
df.job.value_counts(normalize= True).plot.barh()
plt.show()
```



In [47]:
```
df.job.value_counts().plot.barh()
plt.show()
```

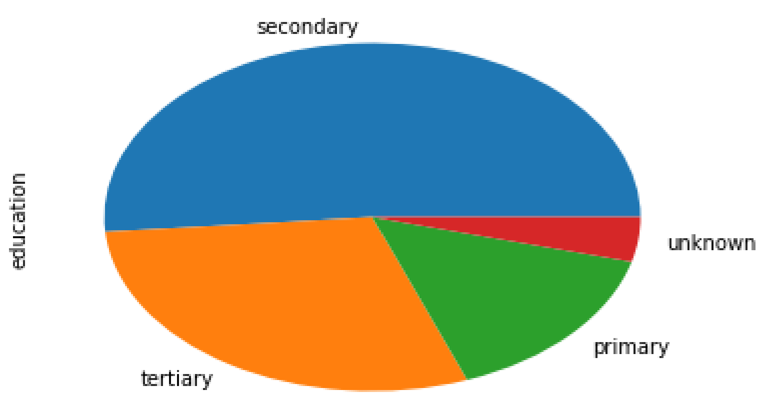


Education variable

In [48]:
```
df.education.value_counts(normalize= True)
```

Out[48]:
```
secondary    0.513222
tertiary     0.294196
primary      0.151490
unknown      0.041092
Name: education, dtype: float64
```

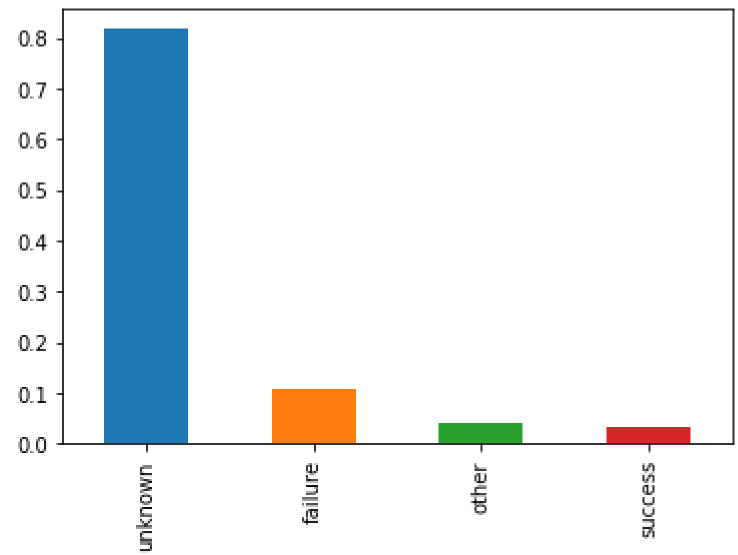
In [49]:
```
df.education.value_counts(normalize= True).plot.pie()
plt.show()
```



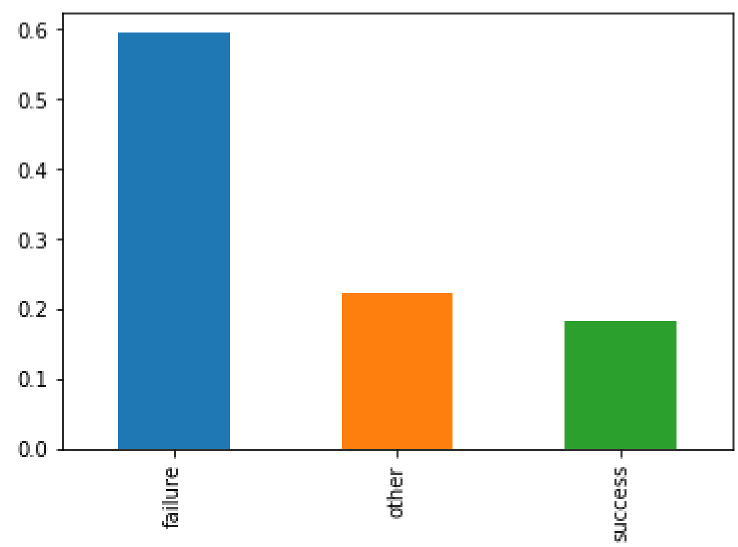
poutcome variable

In [50]:
```
df.poutcome.value_counts(normalize= True).plot.bar()
```

Out[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x19f98e958d0>
```



In [51]:
```
df[~(df.poutcome == 'unknown')].poutcome.value_counts(normalize= True).plot.
plt.show()
```

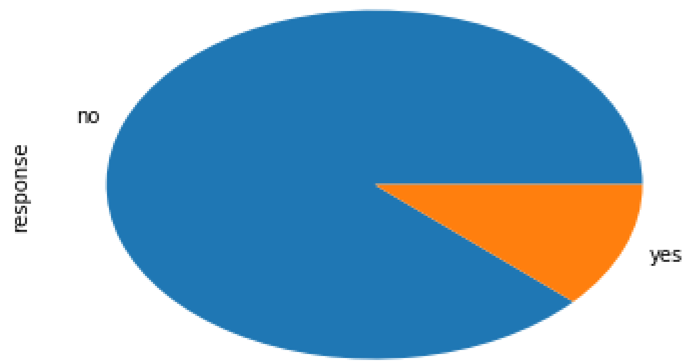


response-the target vaiable

In [52]:
```
df.response.value_counts(normalize= True)
```

Out[52]:
```
no     0.882974
yes    0.117026
Name: response, dtype: float64
```

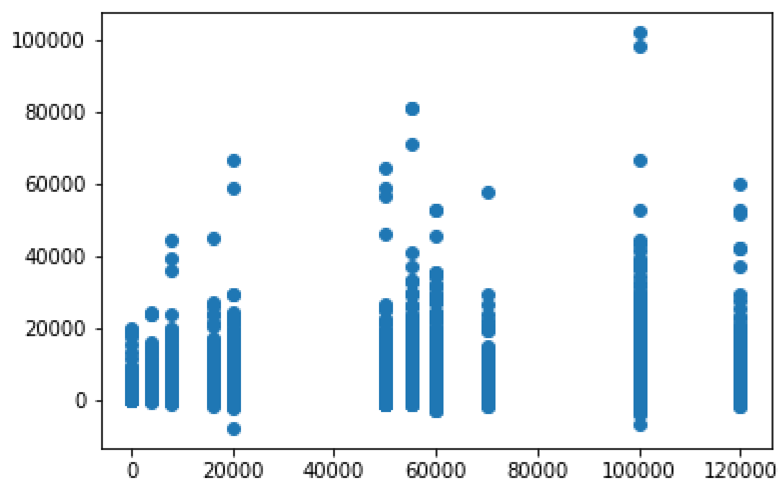
In [53]:
```
df.response.value_counts(normalize= True).plot.pie()
plt.show()
```



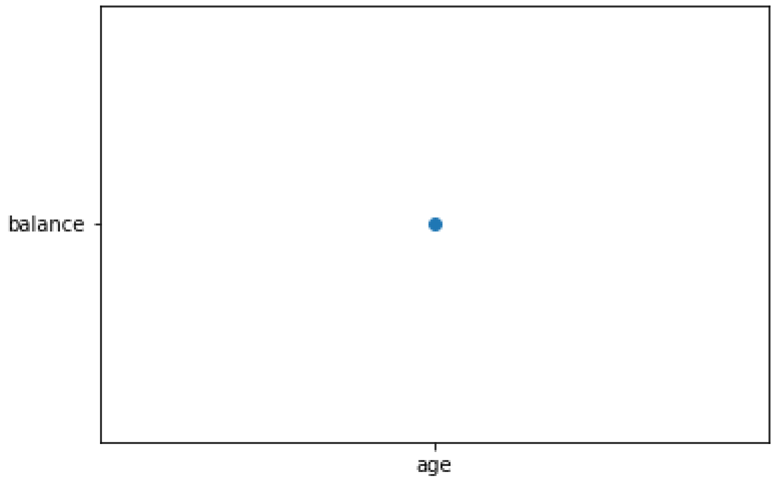
Bivariate analysis

Numerical-numerical

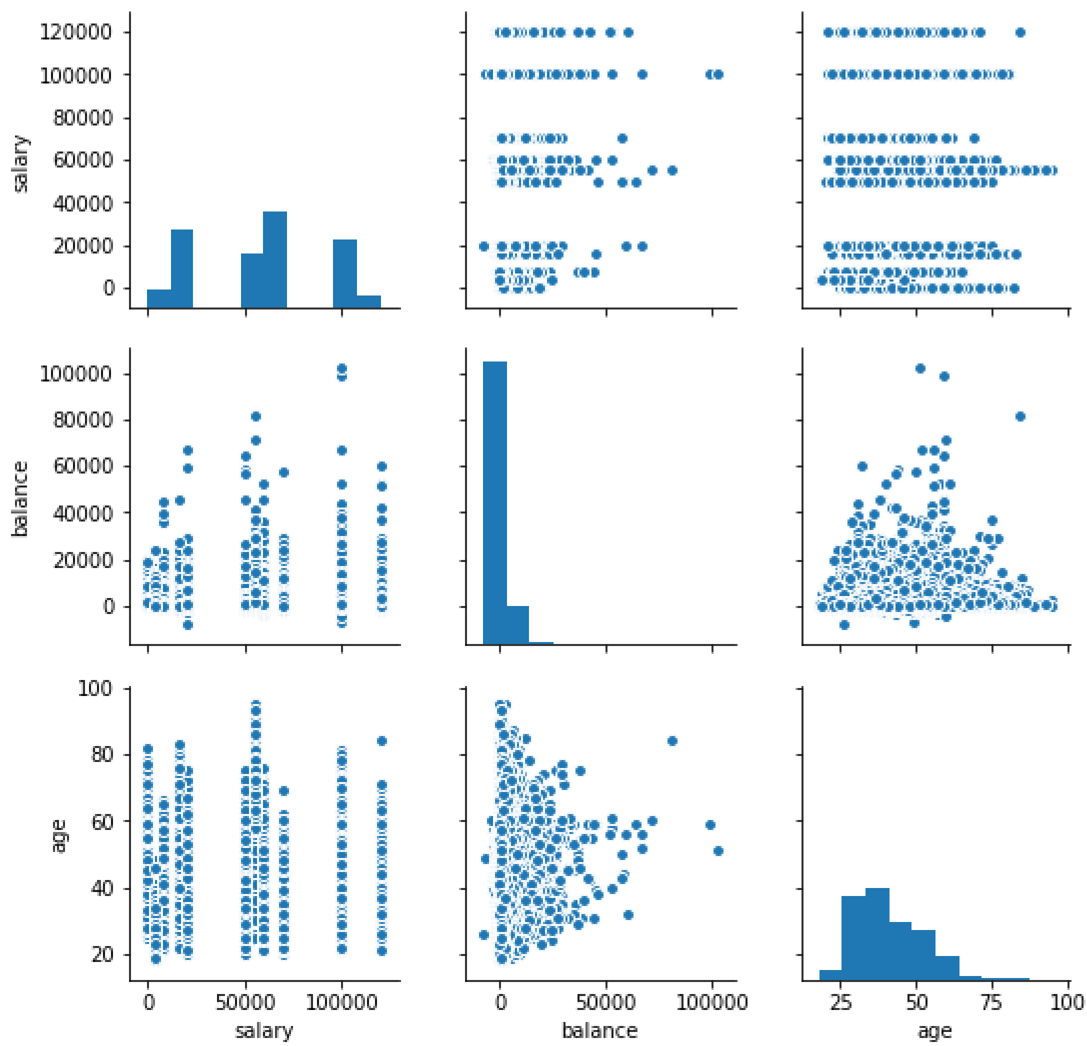
In [54]:
```
plt.scatter(df.salary,df.balance)
plt.show()
```



In [95]:
```
plt.scatter(x="age",y= "balance")
plt.show()
```



In [56]:
```
sns.pairplot(data=df, vars=["salary","balance","age"])
plt.show()
```



Quantity using correlation values

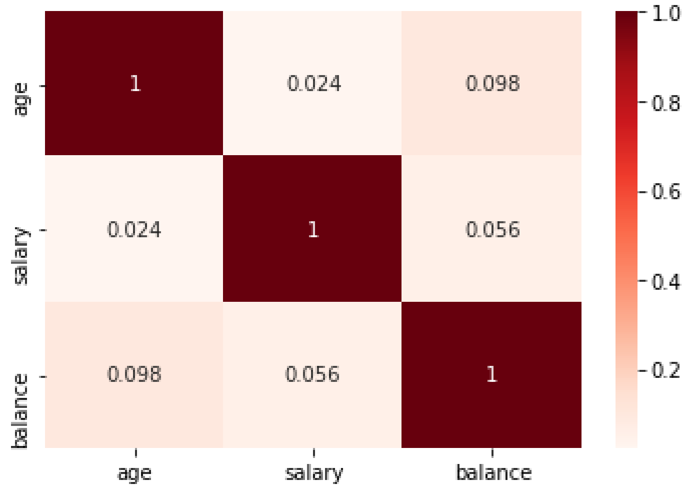
In [57]:
```
df[["age","salary","balance"]].corr()
```

Out[57]:

	age	salary	balance
age	1.000000	0.024374	0.097755
salary	0.024374	1.000000	0.055505
balance	0.097755	0.055505	1.000000

Correlation Heatmap

In [58]:
```
sns.heatmap(df[["age","salary","balance"]].corr(),annot = True, cmap="Reds")
plt.show()
```



Categorical- numerical

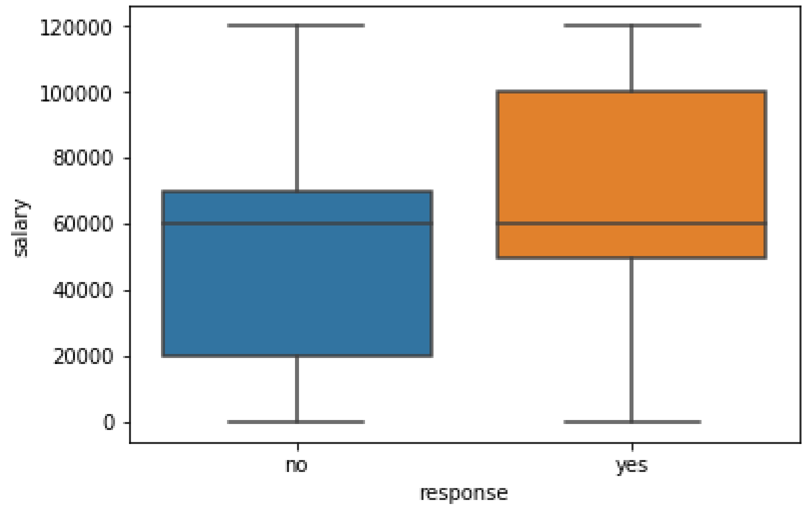
In [59]:
```
df.groupby("response")['salary'].mean()
```

Out[59]:
```
response
no     56769.510482
yes    58780.510880
Name: salary, dtype: float64
```

In [60]:
```
df.groupby("response")['salary'].median()
```

Out[60]:
```
response
no     60000
yes    60000
Name: salary, dtype: int64
```

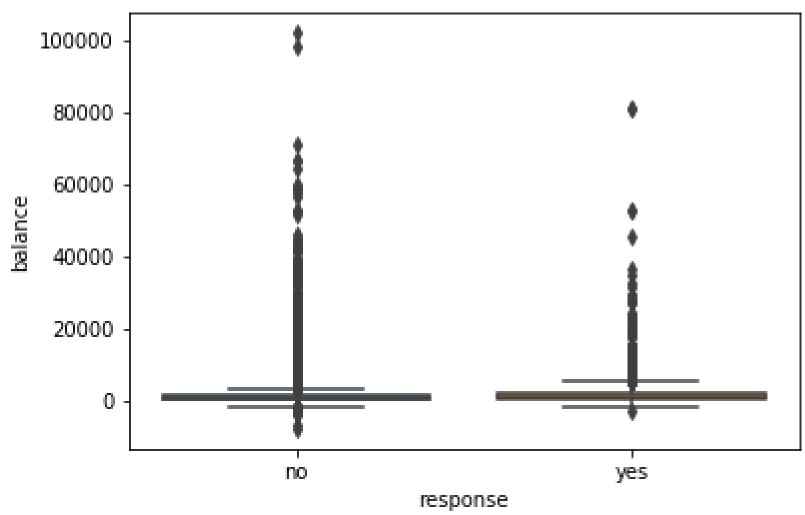
In [61]:
```
sns.boxplot(data= df, x="response", y="salary")
plt.show()
```



Response vs. balance

- we know that balance is highly skewed- has very high value

In [62]:
```
sns.boxplot(data = df, x="response", y = "balance")
plt.show()
```



In [63]:
```
df.groupby('response')['balance'].mean()
```

Out[63]:
```
response
no      1304.292281
yes     1804.681362
Name: balance, dtype: float64
```

In [64]:
```
df.groupby('response')['balance'].median()
```

Out[64]:
```
response
no      417
yes     733
Name: balance, dtype: int64
```

75th percentile

In [65]:
```python
import numpy as np
def p75(x):
    return  np.quantile(x,0.75)

print(p75)
```

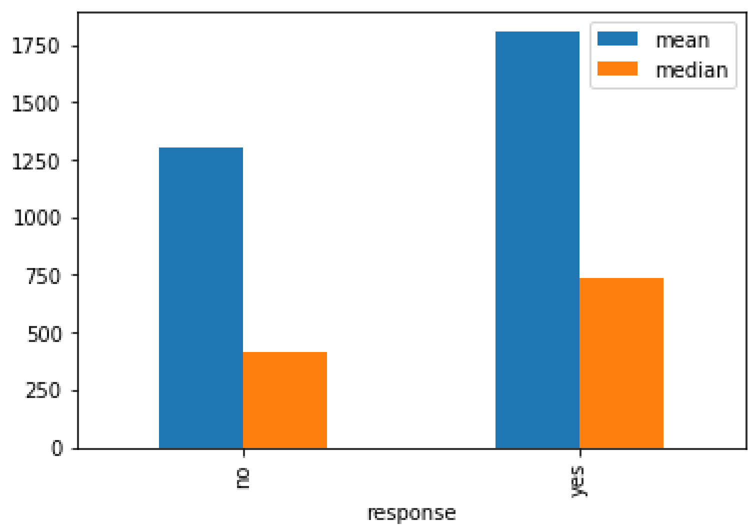
```
<function p75 at 0x0000019F994BBD90>
```

In [66]:
```python
df.groupby('response')['balance'].aggregate(["mean","median"])
```

Out[66]:

response	mean	median
no	1304.292281	417
yes	1804.681362	733

In [67]:
```python
df.groupby('response')['balance'].aggregate(["mean","median"]).plot.bar()
plt.show()
```



In [68]:
```python
df.groupby('education')['salary'].mean()
```

Out[68]:
```
education
primary      34224.510663
secondary    49736.127280
tertiary     82878.300113
unknown      46558.427571
Name: salary, dtype: float64
```

In [69]:
```python
df.groupby('education')['salary'].median()
```

Out[69]:
```
education
primary       20000
secondary     55000
tertiary     100000
unknown       50000
Name: salary, dtype: int64
```

Categorical- categorical

In [70]:
```
df['response_flag'] = np.where(df.response=='yes',1,0)
```

In [71]:
```
df.response_flag.value_counts()
```

Out[71]:
```
0    39906
1     5285
Name: response_flag, dtype: int64
```

In [72]:
```
df.response_flag.value_counts(normalize= True)
```

Out[72]:
```
0    0.883052
1    0.116948
Name: response_flag, dtype: float64
```

In [73]:
```
df.response_flag.mean()
```

Out[73]:
```
0.11694806488017526
```

Education vs. response rate

In [74]:
```
df.groupby(['education'])['response_flag'].mean()
```

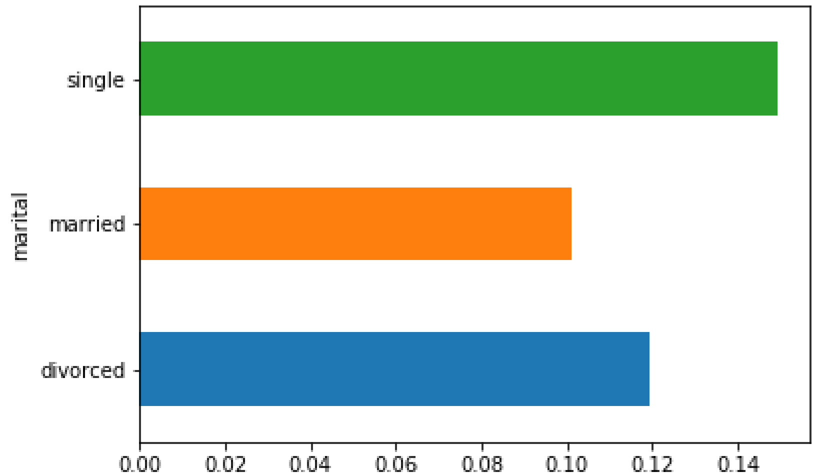
Out[74]:
```
education
primary      0.086328
secondary    0.105549
tertiary     0.149981
unknown      0.135703
Name: response_flag, dtype: float64
```

Marital vs. response rate

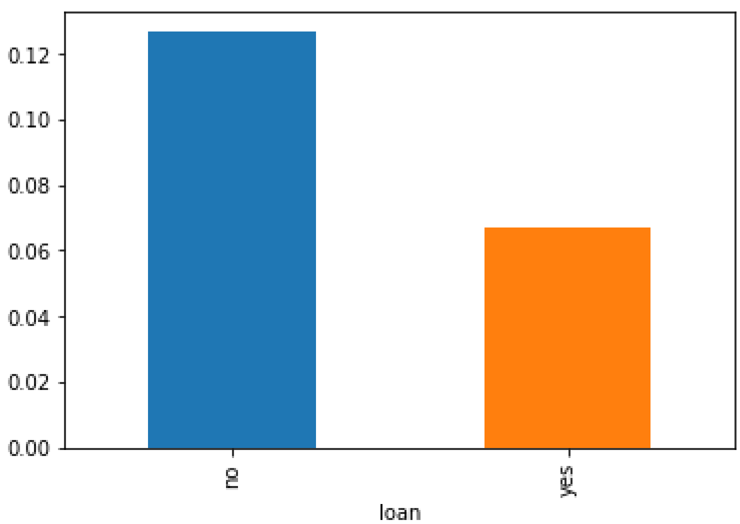
In [75]:
```
df.groupby(['marital'])['response_flag'].mean()
```

Out[75]:
```
marital
divorced    0.119400
married     0.101198
single      0.149460
Name: response_flag, dtype: float64
```

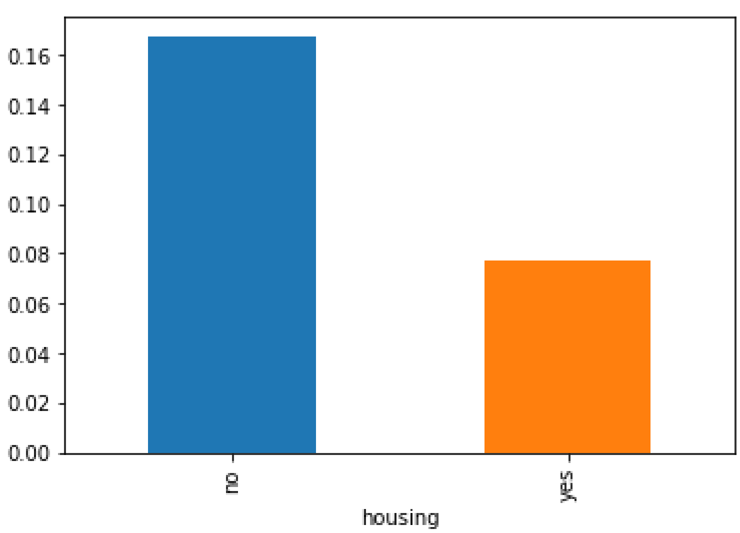
In [76]:
```
df.groupby(['marital'])['response_flag'].mean().plot.barh()
plt.show()
```



In [77]:
```
df.groupby(['loan'])['response_flag'].mean().plot.bar()
plt.show()
```

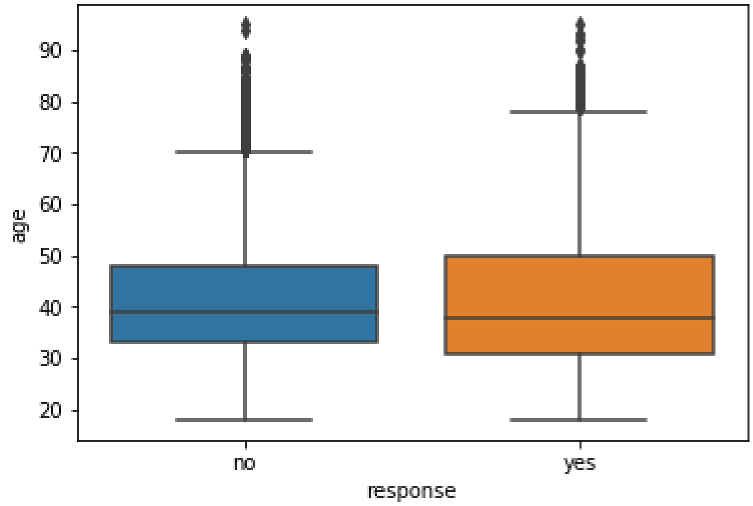


In [78]:
```
df.groupby(['housing'])['response_flag'].mean().plot.bar()
plt.show()
```



Age vs. response

In [79]:
```
sns.boxplot(data= df, x="response", y="age")
plt.show()
```



Making buckets from the age column

In [80]:
```
?pd.cut
```

In [81]:
```
pd.cut(df.age[:5],[0,30,40,50,60,9999], labels=["<30","30-40","40-50","50-60
```

Out[81]:
```
0    50-60
1    40-50
2    30-40
3    40-50
4    30-40
Name: age, dtype: category
Categories (5, object): [<30 < 30-40 < 40-50 < 50-60 < 60+]
```

In [82]:
```
df.age.head()
```

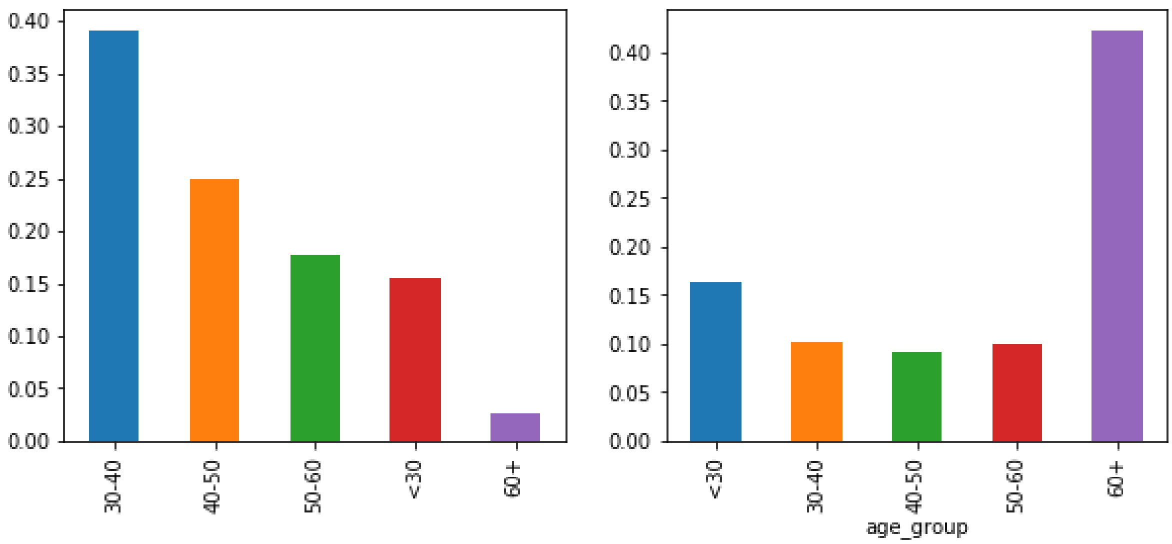
Out[82]:
```
0    58.0
1    44.0
2    33.0
3    47.0
4    33.0
Name: age, dtype: float64
```

In [83]:
```
df['age_group']=pd.cut(df.age,[0,30,40,50,60,9999], labels=["<30","30-40","4
```

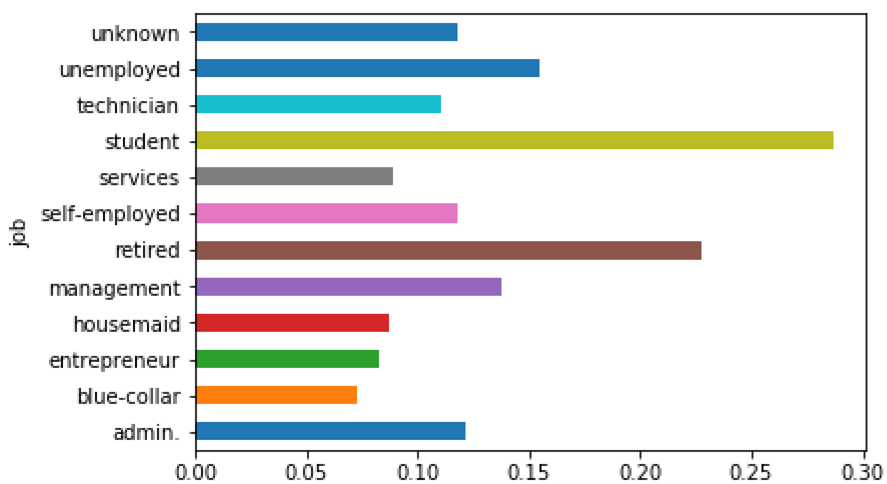
In [84]:
```
df.age_group.value_counts(normalize= True)
```

Out[84]:
```
30-40    0.391206
40-50    0.248611
50-60    0.178376
<30      0.155518
60+      0.026288
Name: age_group, dtype: float64
```

In [85]:
```
plt.figure(figsize=[10,4])
plt.subplot(1,2,1)
df.age_group.value_counts(normalize= True).plot.bar()
plt.subplot(1,2,2)
df.groupby(['age_group'])['response_flag'].mean().plot.bar()
plt.show()
```



In [86]:
```
df.groupby('job')['response_flag'].mean().plot.barh()
plt.show()
```



More than 2 variables

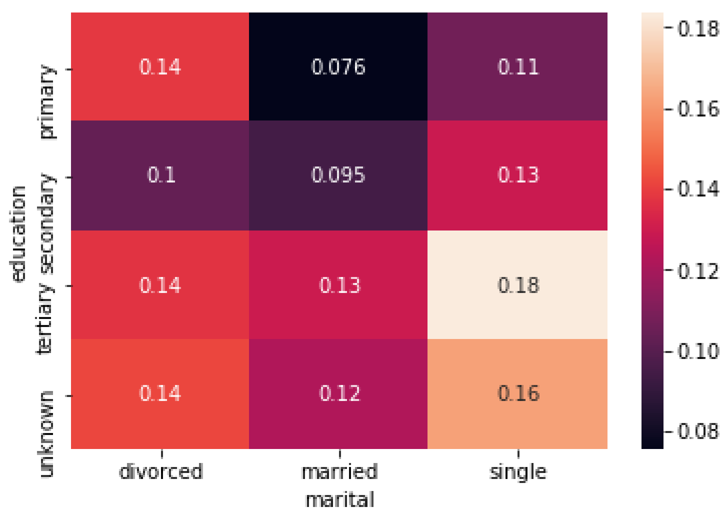
In [87]:
```
res=pd.pivot_table(data= df,index = "education",columns="marital", values="r
res
```

Out[87]:

marital	divorced	married	single
education			
primary	0.138667	0.075515	0.106808
secondary	0.103485	0.094595	0.129213
tertiary	0.137415	0.129761	0.183546
unknown	0.142012	0.122414	0.162879

In [88]:

```
sns.heatmap(res, annot = True)
plt.show()
```



In [89]:

```
sns.heatmap(res, annot = True, cmap= "RdYlGn")
plt.show()
```

In [90]:

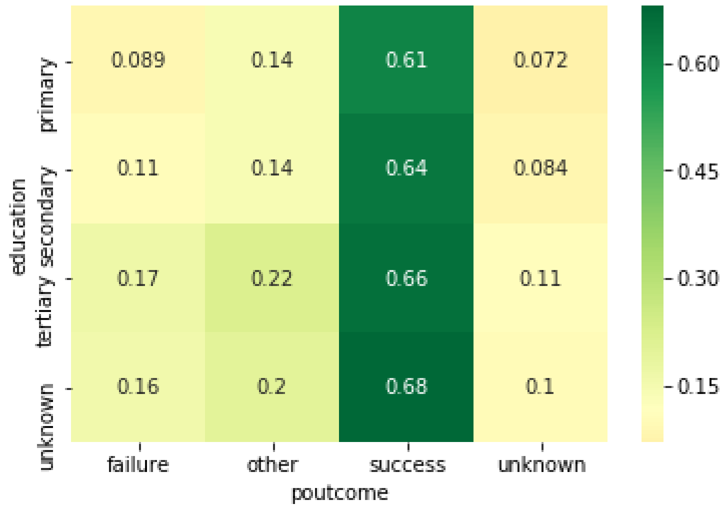
```
sns.heatmap(res, annot = True, cmap= "RdYlGn", center=0.117)
plt.show()
```

Job vs. Marital vs. response

In [91]:
```
res=pd.pivot_table(data= df,index = "job",columns="marital", values="respons
sns.heatmap(res, annot = True, cmap= "RdYlGn", center=0.117)
plt.show()
```

Education vs. poutcome vs. response

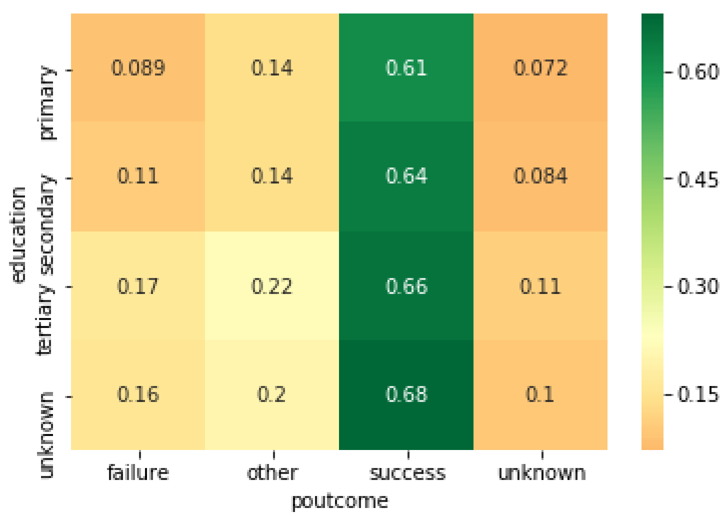
In [92]:
```
res=pd.pivot_table(data= df,index = "education",columns="poutcome", values="
sns.heatmap(res, annot = True, cmap= "RdYlGn", center=0.117)
plt.show()
```



In [93]:
```
df[df.pdays>0].response_flag.mean()
```

Out[93]:
```
0.23061076102762967
```

In [94]:
```
res=pd.pivot_table(data= df,index = "education",columns="poutcome", values="
sns.heatmap(res, annot = True, cmap= "RdYlGn", center=0.2308)
plt.show()
```



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